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Development of an AI-based interactive tool to support radiographer training in chest X-ray analysis

Sviluppo di uno strumento interattivo basato sull'intelligenza artificiale per supportare la formazione dei tecnici di radiologia nell'analisi radiologica del torace

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ABSTRACT The increasing demand for chest X-ray examinations presents challenges in radiography education, requiring scalable and interactive learning solutions. This study presents an AI-based interactive tool designed to enhance radiographer training by providing real-time feedback, anatomical segmentation, and self-assessment features. Twenty-five third-year radiography students evaluated the tool's usability and perceived quality using a validated evaluation framework. The results indicate high learnability (3.12/4), system response time (3.54/4), and security (3.38/4) but highlight areas for improvement in stability (2.79/4) and diagnostic performance (2.79/4). The tool was generally well accepted, with moderate scores perceived benefit (3.02/4) and intention of use (2.75/4). While the AI tool shows promise in enhancing radiography education through interactive learning, further improvements in stability and user interface design are needed for broader adoption. Future studies will assess its impact on learning outcomes and clinical decision-making skills.

KEYWORDS Artificial Intelligence; Chest X-Ray; Radiography Training; Education.

SOMMARIO La crescente domanda di esami radiografici del torace pone sfide nella formazione in radiologia, che richiedono soluzioni di apprendimento scalabili e interattive. Questo studio presenta uno strumento interattivo basato sull'intelligenza artificiale, progettato per migliorare la formazione dei tecnici di radiologia fornendo feedback in tempo reale, segmentazione anatomica e funzionalità di autovalutazione. Venticinque studenti di radiologia del terzo anno hanno valutato l'usabilità e la qualità percepita dello strumento utilizzando un framework di valutazione convalidato. I risultati indicano un'elevata facilità di apprendimento (3,12/4), tempi di risposta del sistema (3,54/4) e sicurezza (3,38/4), ma evidenziano aree di miglioramento in termini di stabilità (2,79/4) e prestazioni diagnostiche (2,79/4). Lo strumento è stato generalmente ben accolto, con punteggi moderati per il beneficio percepito (3,02/4) e l'intenzione d'uso (2,75/4). Sebbene lo strumento di intelligenza artificiale si dimostri promettente nel migliorare la formazione in radiologia attraverso l'apprendimento interattivo, sono necessari ulteriori miglioramenti nella stabilità e nel design dell'interfaccia utente per una più ampia adozione. Studi futuri ne valuteranno l'impatto sui risultati di apprendimento e sulle capacità decisionali cliniche.

PAROLE CHIAVE Intelligenza Artificiale; Radiografia del Torace; Formazione in Radiografia; Educazione.

1. Introduction

A notable increase in chest X-ray examinations has been observed recently, driven mainly by the COVID-19 pandemic (Rubin et al., 2020; Smith-Bindman et al., 2019). At the same time, many radiography educators and students are still coping with the lasting effects of the pandemic on radiography education, with severe consequences in low-resource and resource-constrained settings (Tay & McNulty, 2023). These converging trends have placed significant pressure on the learning process of radiological anatomy, such as chest X-ray interpretation, which primarily relies on practical small-group teaching and tutoring sessions. Given the inherent variability of human anatomy, adequate training in this domain requires analysing a substantial number of diverse imaging cases, pointing out the need for enhanced educational resources and scalable learning methods.

Integrating artificial intelligence (AI) technologies into healthcare education presents a promising solution to chest X-ray interpretation training challenges. Specifically, the literature highlights that AI-based solutions offer multiple advantages: (i) Real-time feedback and assessment on anatomical interpretation, enabling learners to self-assess and continuously improve their skills (Chheang et al., 2024; X. Li et al., 2024) ; (ii) Personalised learning paths by adapting the educational experience based on individual performance, targeting learning on areas where students encounter difficulties (Gligorea et al., 2023; Halkiopoulos & Gkintoni, 2024); (iii) Standardised training, ensuring consistency in the delivery of educational content, reducing variability associated with instructor-dependent teaching methods (Crompton & Burke, 2023; Yu et al., 2024); (iv) Resource efficiency, since the automation of feedback and supervision reduces the need for constant instructor involvement, making training more scalable and accessible, particularly in remote or resource-limited settings (Goel, 2020); (v) and, data-driven insights by the analytics on the track learners' long-term performance, allowing educators to refine curricula and prioritise essential skills based on empirical evidence (Gligorea et al., 2023).

AI-based radiography education tools provide personalized and scalable training by acting as virtual mentors with explainable feedback with anatomic heat maps and natural language explanations, or Alteach platform that simulates patient interactions, also using natural language processing (M. D. Li & Little, 2023). Others like the Adaptive Radiology Interpretation and Education System (ARIES), allow users to compute disease probabilities from imaging features. AI can also curates comprehensive digital teaching file databases, customising case selection to align with trainees' educational needs and subspecialty interests (Duong et al., 2019; M. D. Li & Little, 2023). Beyond case-based learning, AI allows simulation environments in CT and MRI, offering preclinical training in scan planning, image acquisition, and reconstruction in radiographer education (Chaka & Hardy, 2021), and complemented with virtual reality provides physical-virtual hybrid simulations improving student engagement and learning outcomes (Acosta & López, 2024). Conversational AI, for example ChatGPT, serve as on-demand tutor for scenario creation, assessment design, and collaborative learning (Amedu & Ohene-Botwe, 2024).

Despite advances in AI-driven radiography training, existing tools typically rely on static overlays or instructor-mediated feedback, lack multi-scale anatomical segmentation, and are confine to proprietary software and case libraries. Few platforms provide real-time segmentation overlays that students can directly compare to their own annotations, nor do they allow access to heterogeneous image sources, such as open-access repositories (e.g. PadChest, CheXpert) or user-uploaded DICOMs, within a scalable, browser-based environment, Consequently, learners are unable to engage in self-paced, data-driven practice across the full spectrum of clinical variability, pointing for a critical need for an interactive, web-native platform that integrate automated segmentation, real-time feedback and unrestricted image ingestion.

This study aims to explain the conception and development of an AI platform to support chest X-ray anatomy training by providing real-time feedback, personalised learning paths, and standardised assessment methods. It also aims to assess the platform's usability and perceived quality among undergraduate medical imaging students. The article focuses on the AI tool's technical design, implementation challenges, and functional capabilities, highlighting its potential to enhance medical imaging education through automated analysis and interactive learning features.

2. Methodology

This section describes our methodology in two parts. First, it presents the design and architecture of the proposed interactive AI-based tool for radiographer training. Second, it presents the study design developed to assess the usability and perceived quality of the first version of the AI-based tool.

2.1. Design and Architecture of the AI-based tool

2.1.1. System Overview

The tool is a web-based platform designed and implemented to facilitate radiographer training in chest X-ray analysis. The platform combines modern digital technologies with AI to provide radiography students with an immersive, hands-on learning experience.

An existing library of pre-trained state-of-the-art AI algorithms is specifically leveraged to automatically obtain anatomical segmentations of chest X-rays and identify many anatomical regions, such as the lungs, heart, and spine. The platform supports iterative learning by enabling direct comparisons between user annotations and AI-generated segmentations.

2.1.2. Core Features and Use Cases

The proposed tool's key points are its ease of use, interactiveness, and personalisation, which are provided by various features and mechanisms. As illustrated in Figure 1, users can start practising analysing X-rays from the home page by interactively identifying and selecting anatomical regions. Once a specific area has been selected (see Figure 2), the selection is quantitatively evaluated based on AI-generated segmentations of the X-rays using the Dice coefficient.

This score is shown to the user, providing insights into their performance. The segmentation generated by the AI algorithm is additionally overlaid onto user selections to provide valuable feedback. AI and user selections are coloured green and red, respectively, to highlight areas of consensus and discrepancies (see Figure 3).

Moreover, practices can be carried out on X-rays provided by the tool for quick and easy set-up, or the user can upload new X-rays for personalisation. In the latter case, the ability to generalise the AI algorithm allows the provision of segmentations on unseen uploaded X-rays.

Finally, personalisation is further enriched by providing two modes: practising various anatomical regions one X-ray at a time or training to identify a specific anatomical area of their choice on several X-rays. The former allows extensive practice in identifying many areas, while the latter provides for a specific focus on a particular region.

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Figure 1. Home page of the platform prototype. It is composed of a short introduction and buttons to access the exercises.

2.1.3. Technical Design

The platform employs a standard three-tier architecture, dividing the system into three layers: a presentation tier (a.k.a. user interface or front-end), a logic tier (a.k.a. service or back-end), and a data tier, as shown in Figure 4.

The user interface is a web application built using Jinja2 templates. It enables the dynamic generation of web pages based on user input and back-end responses. This structure ensures a seamless user experience with responsive and interactive design elements.

The backend coordinates the overall system by serving content to the web application, receiving user inputs, running the AI algorithm as needed, and responding with the results. Moreover, it handles data management, including storing X-rays, user annotations, and feedback with the support of the data layer. Technically, the backend is implemented in Python and uses Flask, ensuring a lightweight, scalable framework for handling server-side logic. X-ray analysis relies on the TorchXRayVision library (Cohen et al., 2020, 2022). In particular, PSPNet (Lian et al., 2021) is leveraged to generate segmentations of anatomical regions from X-ray images, as detailed in Figure 5.

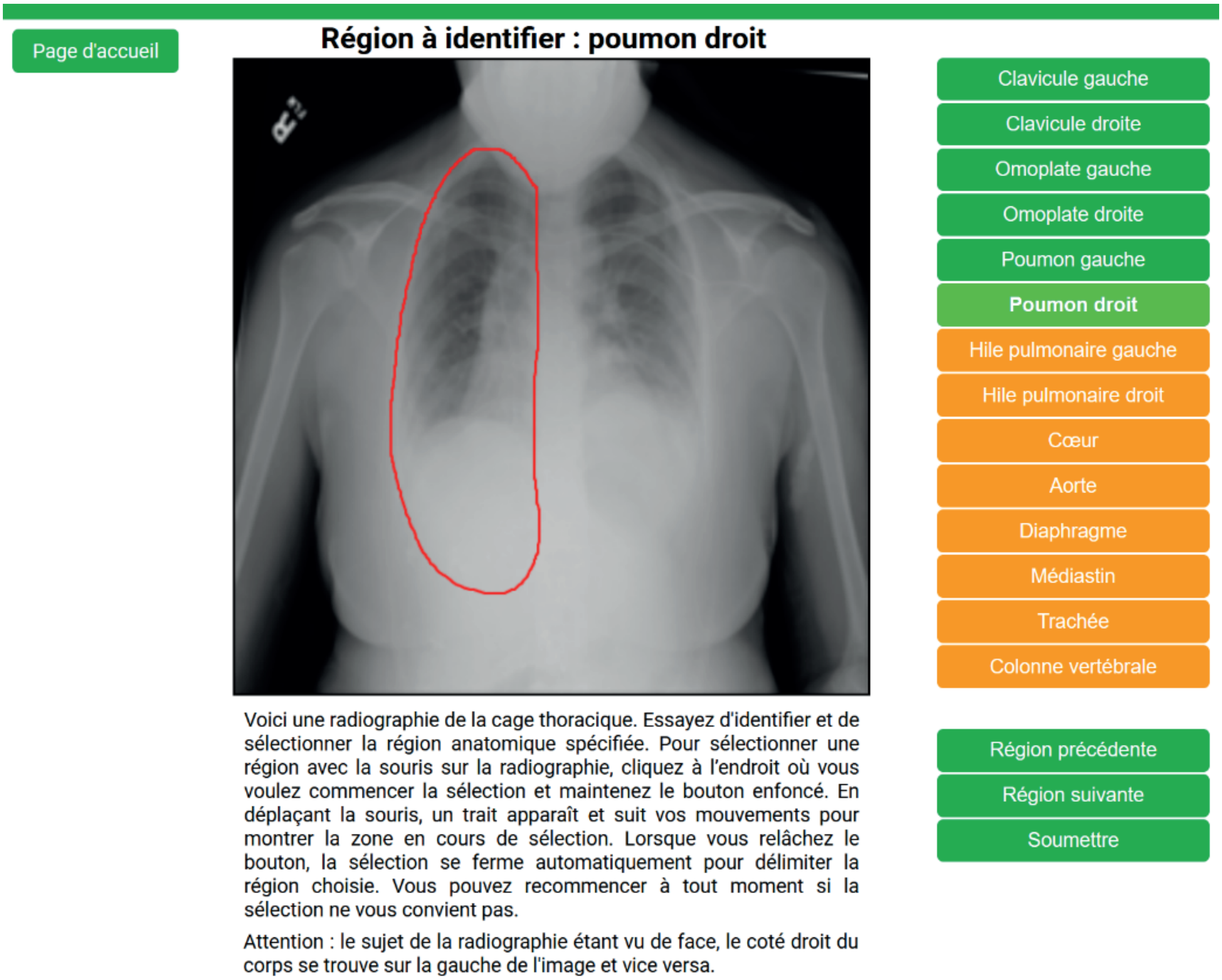

Figure 2. Exercise page: The user is asked to identify and select various anatomical areas (the right lung is supposedly chosen here).

The data layer is implemented following a hybrid approach: X-rays are stored in a file-based system for efficient retrieval and access, and segmentation masks and other metadata are stored in a relational database managed using PostgreSQL, ensuring a balance between performance and scalability. A set of predefined X-rays is made available to the user so that they can practice without having to provide them themselves. To this end, the PadChest dataset –a comprehensive open-source collection of chest X-rays with varied anatomical and pathological presentations – is the primary source of chest X-rays.

2.1.4. Data Privacy and Security

Handling medical data necessitates stringent data privacy and security measures. To this end, the current version of the proposed tool follows the principle of simplicity in cybersecurity. First, no personal data is ever asked or collected. Second, the only kind of user input is the X-rays that can be uploaded. These images stored as files are systematically renamed and solely processed by the AI algo-

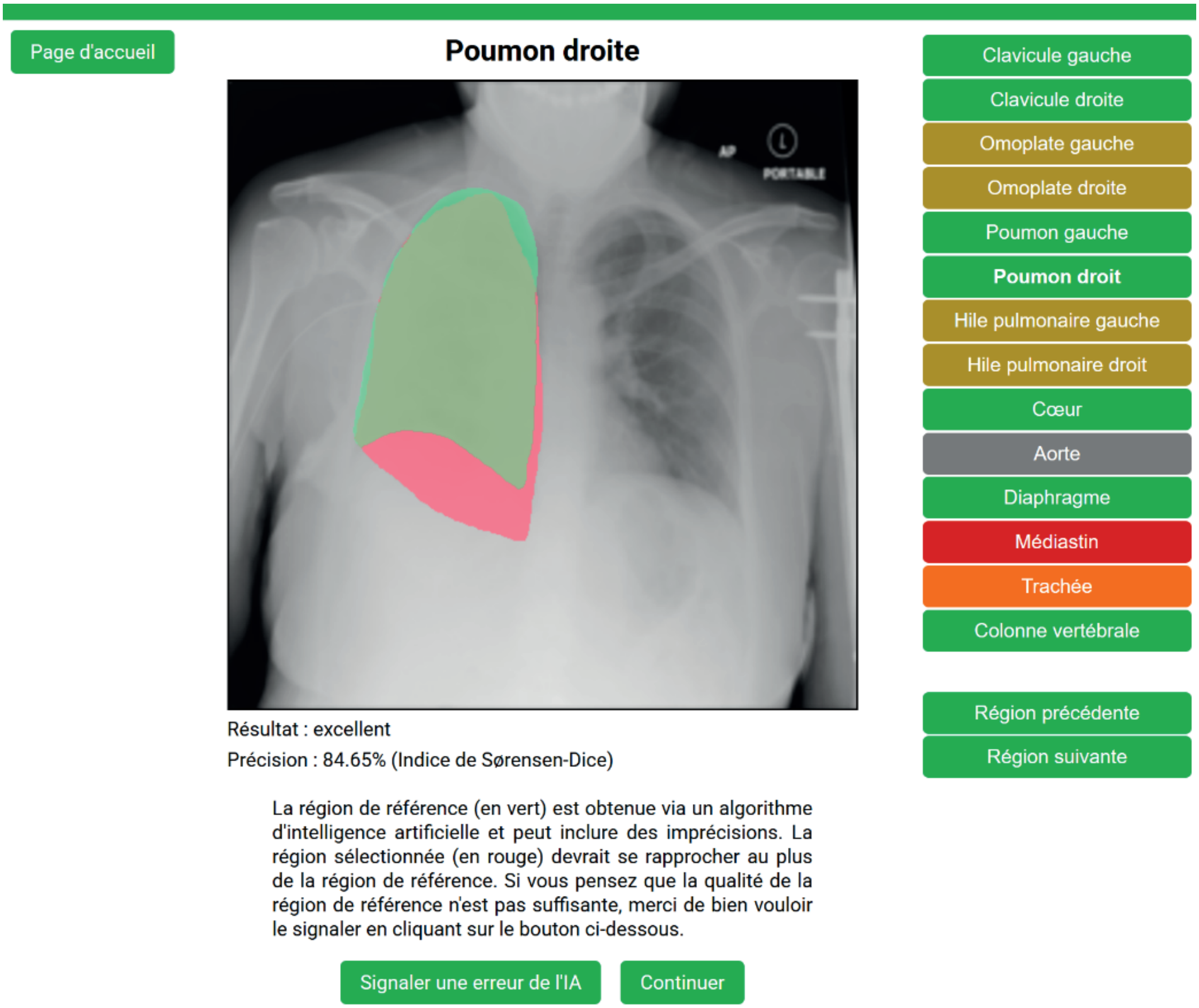

Figure 3. The results page provides insights into the student's performance. Visual feedback compares the red area (user-selected) with the green area (AI-segmented), while a performance score is based on the Dice-Sørensen coefficient.

rithm from TorchXRayVision to prevent cyberattacks or denial of service. Finally, web sessions do not contain sensitive data and are exclusively managed on the server side to avoid session hijacking.

2.2. Study design to assess the usability and perceived quality of the AI-based tool

A user evaluation study was conducted with a convenience sample (N) of 25 undergraduate students in their third year of a radiography bachelor's program to assess the usability and perceived quality of the first version of the AI-based chest X-ray training application. These participants were recruited from a university setting and voluntarily agreed to participate in the study.

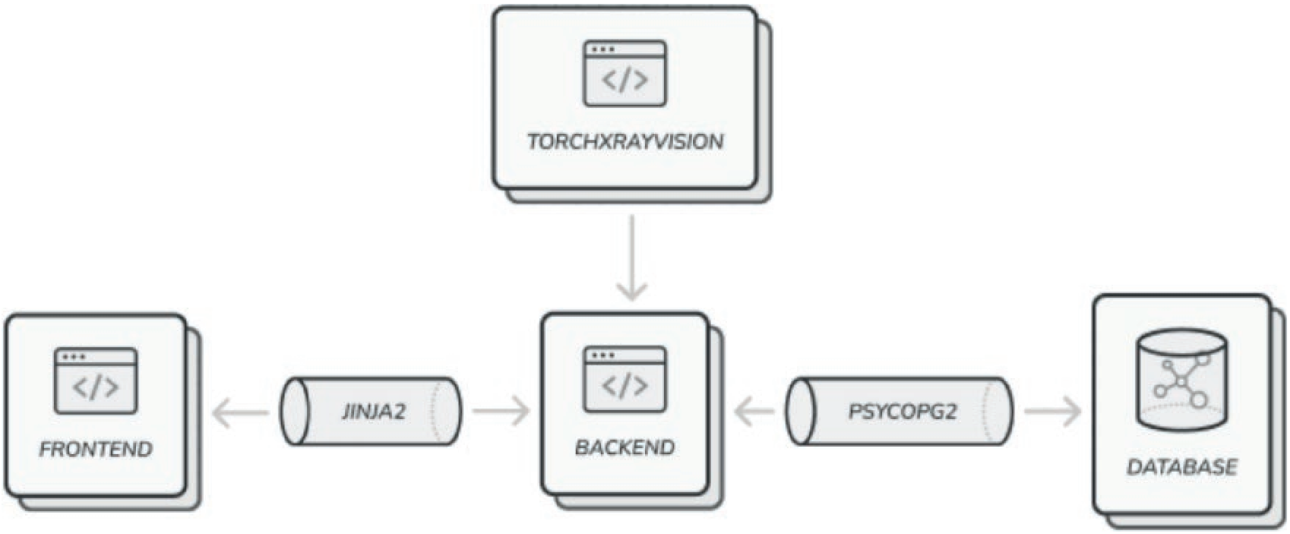

Figure 4. The application three-tier system diagram showing the UI/web front-end, the backend with the AI engine (TorchXRayVision, PSPNet), and data/storage layer (PadChest dataset, PostgreSQL).

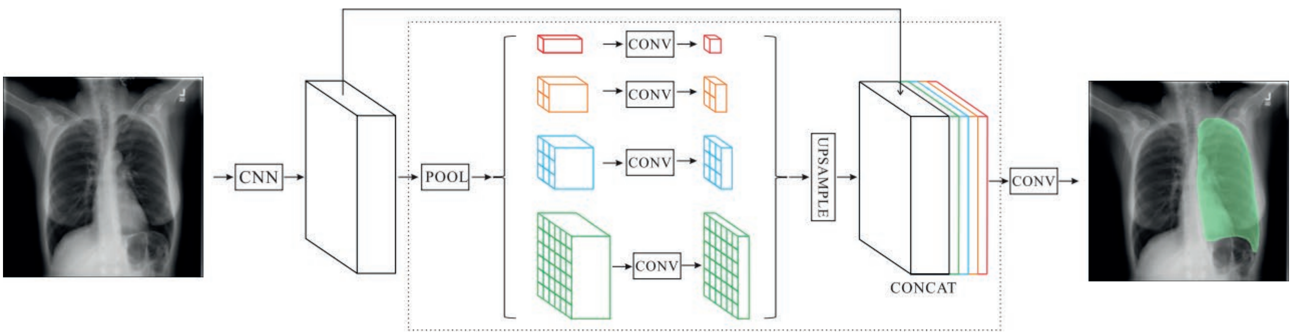

Figure 5. PSPNet segmentation pipeline: a chest X-ray is fed through a CNN backbone to produce feature maps, which undergo multi-scale pooling (1×1, 2×2, 3×3, 6×6), convolution, upsampling, and concatenation before a final convolution generates the lung segmentation mask overlaid on the original image.

2.2.1. Procedure

After briefly explaining the application, participants were given 30 minutes to explore it, utilising its functionalities across different exams and anatomical regions of the chest. After this hands-on experience, they were asked to evaluate the application using the evaluation framework for successful artificial intelligence-enabled clinical decision support systems proposed by (Ji et al., 2021). This framework includes 22 items, categorised into six key dimensions: perceived ease of use, system quality, information quality, service quality, acceptance and perceived benefit. A 4-point Likert scale was used to rate each item: 1=strongly disagree, 2=disagree, 3=agree, 4=strongly agree.

2.2.2. Ethical considerations and data analysis

This study used the principles outlined in the Declaration of Helsinki and adhered to ethical research guidelines. Participants received oral information regarding the voluntary nature of participa-

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tion and provided informed consent before participating in the evaluation. To ensure data privacy, all collected responses were anonymised before analysis.

The collected data were analysed using descriptive methods, including mean, standard deviation (SD) and median for all ordinal questionnaire items and frequency distribution analysis to assess response patterns across different dimensions. All statistical analyses were conducted using Python-based libraries.

3. Results

Across all questionnaire items, median scores were uniformly 3.00 (“agree”), reflecting a general positive agreement with the application evaluated items, except for system response time in the System Quality dimension, which had a median of 4.00. Thus, mean (SD) are reported here to capture more discrete differences in user tendencies.

Within the usability and perceived ease of use dimension, the application’s learnability received a mean score of 3.12 (0.77), indicating that most users found it relatively easy to learn. However, operability showed a slightly lower result of 2.84 (0.61), suggesting that its usability could be enhanced while the application is learnable. Similarly, the user interface was rated at 2.68 (0.61), reflecting the need for improvement in terms of design intuitiveness and user-friendliness. Data entry and advice display scored 3.04 (0.60) and 3.08 (0.84), respectively, showing moderate satisfaction with these functionalities. The legibility of text and information was rated at 3.24 (0.65), suggesting that the application’s information presentation was clear and readable.

As shown in Table 1, the overall system quality received a mean score of 3.17 (0.77). System response time achieved the highest mean of 3.54 (0.58), mirroring its elevated median of 4.00 and indicating that users found processing and result display efficiency particularly satisfactory. Conversely, stability was among the lower-rated aspects at 2.79 (0.76), highlighting concerns about system crashes or operational inconsistencies.

Users rated information quality at 3.08 (0.64), while security, particularly critical for applications handling sensitive medical data, was given a high score of 3.38 (0.63), reflecting confidence in the system’s data protection measures. However, diagnostic performance was rated at 2.79 (0.5), suggesting that users perceived limitations in the AI’s accuracy and reliability in analysing chest X-ray images.

The service quality rating was 2.89 (0.73), and the operation and maintenance rating was 2.96 (0.69), indicating moderate satisfaction with system support and updates. Information updating scored 2.83 (0.76), emphasising the need for more timely updates.

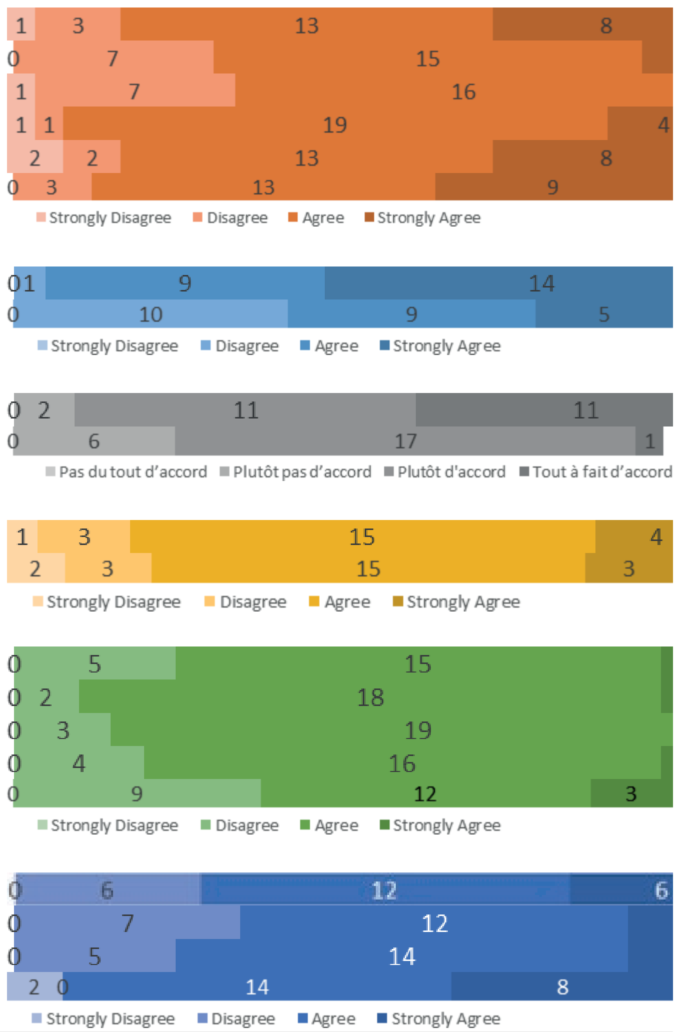
User acceptance of the application was 2.96 (0.58), and expectations confirmation scored 3.00 (0.63), suggesting that while users generally found the tool acceptable, it did not exceed their expectations. Satisfaction with system, information, and service quality ranged from 2.96 to 3.08, indicating an overall neutral-to-positive perception.

The application’s intention of use was rated 2.75 (0.66), indicating that while some users were inclined to continue using it, others were hesitant. Perceived benefit, a critical measure of the application’s usefulness in educational settings, was scored at 3.02 (0.72). Changes in clinical decision-making behaviour (3.00, 0.71), productivity (2.92, 0.7), and adherence to standards (3.00, 0.65) suggest a moderate impact on workflow protocols. Significantly, changes in outcomes improved slightly, with a rating of 3.17 (0.8).

All described results are summarised in Table 1. to allow a systematic evaluation of the AI-based Chest X-ray training tool.

Table 1. Summary of user evaluation results for the AI-based Chest X-ray training application, presenting mean (SD) and median scores across key dimensions of usability, system quality, information and service quality, acceptance and perceived benefit.

Dimensions and items	Mean (SD); Median	Frequency distribution
Perceived ease of use	**3.00 (0.71); 3**	
Learnability	3.12 (0.77); 3	
Operability	2.84 (0.61); 3	
User interface	2.68 (0.61); 3	
Data entry	3.04 (0.60); 3	
Advice display	3.08 (0.84); 3	
Legibility	3.24 (0.65); 3	
System quality	**3.17 (0.77); 3**	
Response time[1]	3.54 (0.58); 4	
Stability[1]	2.79 (0.76); 3	
Information quality	**3.08 (0.64); 3**	
Security[1]	3.38 (0.63); 3	
Diagnostic Performance[1]	2.79 (0.50); 3	
Service Quality	**2.89 (0.73); 3**	
Operation and Maintenance[2]	2.96 (0.69); 3	
Information Updating[2]	2.83 (0.76); 3	
Acceptance	**2.96 (0.58); 3**	
Expectations confirmation	3.00 (0.63); 3	
Satisfaction of System quality[1]	3.08 (0.49); 3	
Satisfaction of information quality[1]	2.96 (0.45); 3	
Satisfaction of service quality[1]	3.00 (0.58); 3	
Intention of use[1]	2.75 (0.66); 3	
Perceived Benefit	**3.02 (0.72); 3**	
Changes in order behavior[1]	3.00 (0.71); 3	
Productivity[1]	2.92 (0.70); 3	
Adherence to standards[1]	3.00 (0.65); 3	
Changes in outcomes[1]	3.17 (0.80); 3	



[1] N = 24 due to one missing response. [2] N = 23 due to two missing responses. [a] N varies by item due to occasional missing data; all other items are based on the full sample of 25.

4. Discussion

The proposed AI-based Chest X-ray platform was successfully developed, deployed in RadiologIA and tested for its usability and perceived quality. The results indicate that the platform has demonstrated strengths in learnability, system response time, security, and areas for improvement in stability, user interface design, and performance.

The platform is innovative because it delivers real-time, interactive feedback not commonly found in traditional medical imaging training tools. The platform enhances engagement using state-of-the-art AI algorithms to generate anatomical segmentation and compare these directly with user annota-

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tions. It promotes a continuous cycle of self-assessment with real-time evaluation. This student-centric approach to the learning process is aligned with the findings of (Ji et al., 2021), where user acceptance is a central determinant of the application success, and it is influenced by perceived ease of use, system quality, information quality, service quality, and perceived benefit. In this study, perceived ease of use (learnability and operability), information quality and changes in outcome were perceived as positive, which aligns with the literature since perceived ease of use was found to be a primary predictor of learner engagement with AI tools (Müssener et al., 2020). Such positive perceptions may suggest that the potential educational impact of the tool is significant. On the one hand, standardising the training process can provide a consistent framework for learning, which can lead to improved skill acquisition among novice medical imaging students. Conversely, the interactive design may promote active learning and autonomy, allowing students to practice repeatedly in a controlled yet flexible environment.

The employed methodology ensured a structured and quantifiable evaluation of the application's usability and performance, providing key insights for future improvements and development interactions. One primary concern is the adoption by educators and students. The moderate ratings for diagnostic performance and intention of use suggest that while AI can support radiography education, users remain sceptical of its reliability in real-world educational applications. These findings resonate with previous studies on AI in medical imaging education (Crotty et al., 2024; M. D. Li & Little, 2023; Simpson & Cook, 2020), which caution against over-reliance on AI and emphasise the need for human oversight and validation, as well as the critical impact that perceived accuracy as on trainee trust and sustained use of automated analysis systems (Chen et al., 2023). Convincing stakeholders to transition to an AI-enhanced approach requires evidence of improved learning outcomes and usability. Moreover, the relatively low stability score raises concerns about system robustness, essential for the application where real-time functionality and reliability are paramount. This suggests that technical optimisations are needed to ensure the long-term sustainability of the tool and reduce errors. Ethical considerations and transparent discussions about AI's constraints will be crucial to encourage its adoption, as well as user training workshops on how to integrate AI into their learning process to mitigate scepticism.

Despite the promising results, this study reveals several limitations. First, it relied on a convenience sample of 25 third-year radiography students from a single institution, limiting generalisability. Second, the evaluation captured only immediate usability and perception metrics without assessing actual learning improvement or long-term retention. Third, the platform prototype did not undergo stress-testing under concurrent use, further system stability is needed. Finally, potential bias in the AI segmentation model was not formally assessed, stressing the need for future work on algorithmic fairness and robustness.

Under the "ChestXLAIrning" project, the next steps are to improve the technical findings report in this study, to evaluate the tool's effectiveness in enhancing learning outcomes—specifically, its impact on radiological anatomical knowledge and the interpretation of chest X-ray images—and finally, to assess the tool's acceptance, usability, and adoption among medical imaging students. The ChestX-LAIrning project aims to transform radiology education by integrating independent learning and improving clinical competencies through AI technology.

5. Conclusions

The development of our AI-based interactive tool can advance medical imaging education, offering a scalable solution that integrates real-time feedback and interactive learning into radiographer training. Through a comprehensive design process that combines modern web technologies with state-of-the-art AI algorithms, the platform provides a unique opportunity for students to engage in self-assessment and skill development with minimal instructor supervision. This innovative approach not only standardises the learning experience but also holds the promise of transforming traditional training methodologies, paving the way for more effective, data-driven, and autonomous education in the field of medical imaging.

Future studies will include improving the technical limitations illustrated in this study, evaluating the tool's long-term impact on learning outcomes and decision-making behaviour, and exploring strategies for optimising AI-human collaboration in radiography training.

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